

Spectral Compression for Remote Sensing Using Principal Component Analysis

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- ... and many others

Rationale / Need for Speed

 RT models required for generating simulated radiances from satellite, ground-based and other platforms

 In retrieval applications, RT models also needed to calculate Jacobians

OSSEs and climate models require massive RT modeling over wide spectral ranges

RT calculations computationally expensive

 New generation LEO and GEO satellites expected to generate data at rates current computing power is unlikely to match

Why is RT Computationally Expensive?

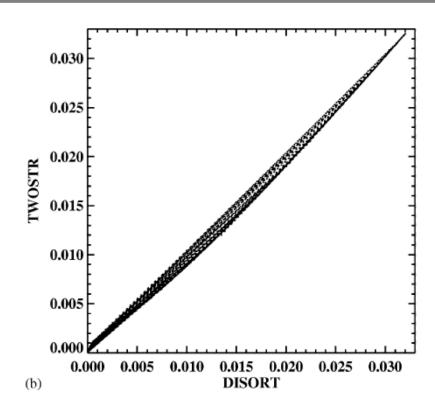
- Wavelengths
 - Spectral points where radiances must be evaluated

- Angles
 - Computational quadrature angles ("streams") at each spectral point

A good solution should address BOTH the above considerations.

Angles

- Separation of single and multiple scattering
 - Large number (sometimes >> 100) of streams required to resolve accurately anisotropy due to scattering
 - Computational burden ~O(M³)
 - Large part of anisotropy of radiation field captured by single scattering
 - Single scattering calculation computationally efficient
- Correlation between multi-stream and two-stream calculations



Natraj et al., 2005

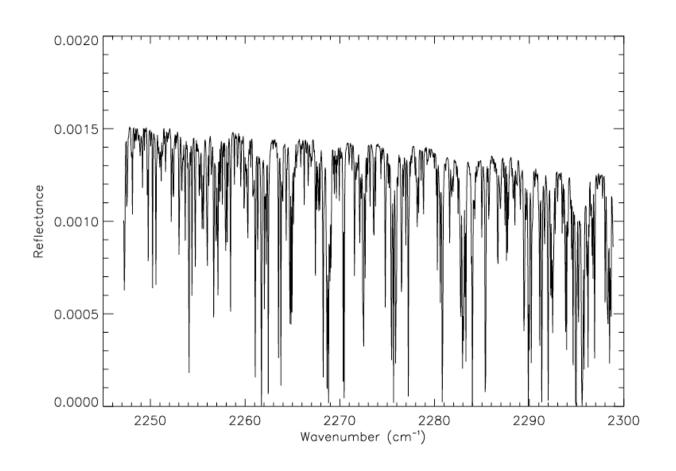
$$I_{PCA}(\lambda) = [I_{2S}(\lambda)]C(\lambda) + \bar{I}_{FO}(\lambda)$$

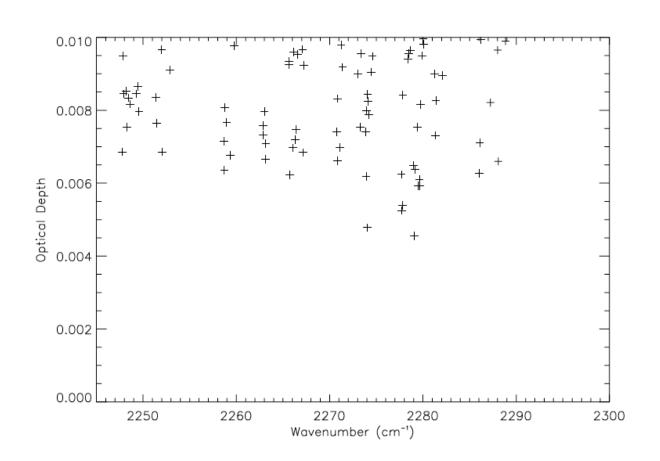
Wavelengths

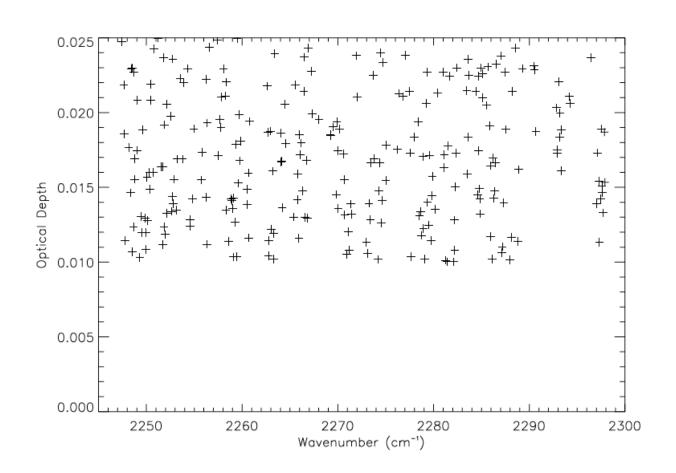
Spectral binning

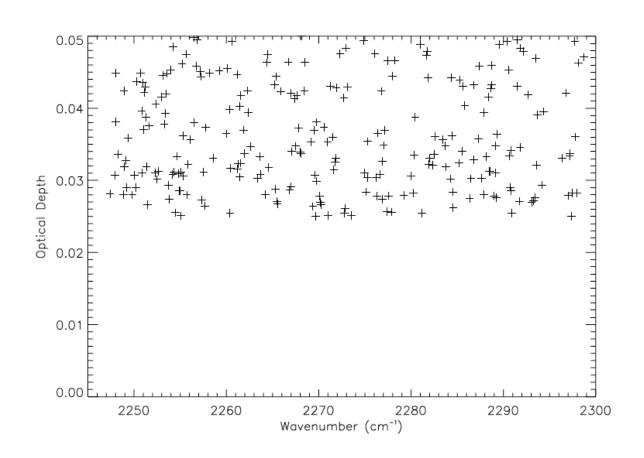
Eigenvalue problem solution

Radiance back-mapping



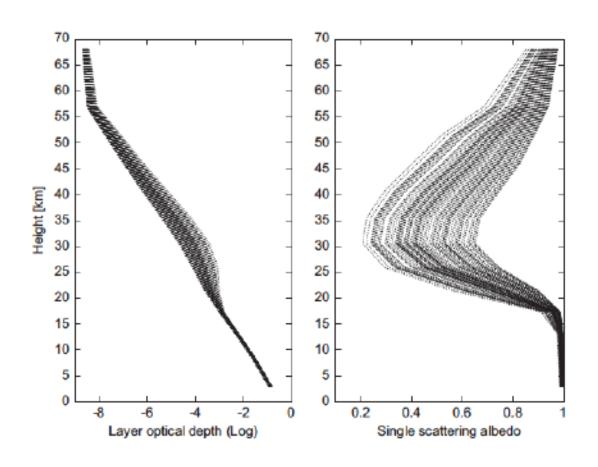








RT Data Set





Eigenvalue Problem Solution: PCA

- Data Set
 - Optical properties in M atmospheric layers at N wavelengths

- Empirical Orthogonal Functions (EOFs)
 - Eigenvectors of covariance matrix of detrended (mean removed) data set
 - New basis to represent original data
 - No loss of information

- Principal Component Scores/Weights
 - Projection of original data set onto EOFs



Eigenvalue Problem Solution: PCA

PCA is an orthogonal transformation

EOFs uncorrelated (original data set strongly correlated)

EOFs sorted in order of decreasing variance accounted for

First few (typically <= 4) EOFs capture > 99.99% of variance

PCA gives insight into variability patterns in data sets



Eigenvalue Problem Solution: PCA

 Mean and EOFs define much smaller set of PCA-projected optical states compared to original data set

Multiple scattering (MS) simulations performed only on reduced set

Fast two-stream model approximates MS contribution at each spectral point

 Correction factors developed based on RT calculations at PCAprojected optical states

Single scatter calculations performed at each spectral point



Radiance Back-Mapping

Radiances for mean bin values: I_{exact}, I_{2S}

$$I_d = \ln(I_{exact}/I_{2S})$$

- EOF-perturbed ratios: I_d^+ , I_d^-
- First and second order differences

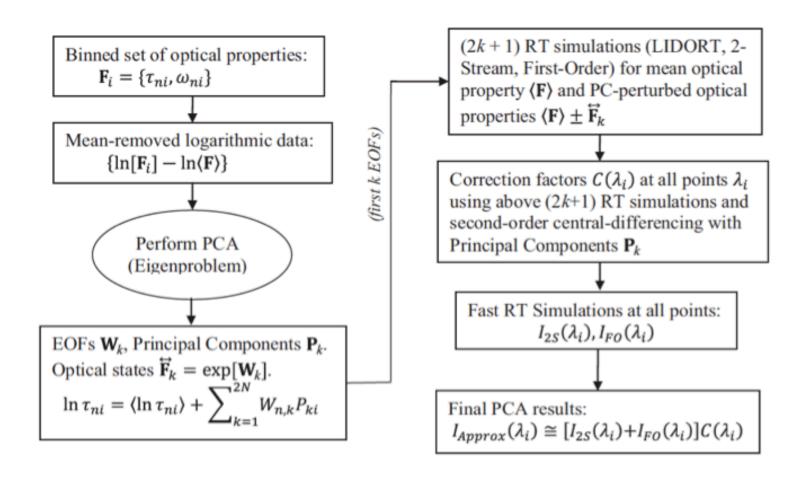
$$\delta I_k = \frac{I_d^+ - I_d^-}{2}$$

$$\delta^2 I_k = I_d^+ + I_d^- - 2I_d$$

Corrected MS radiance

$$I_l = I_l^{2S} \exp \left[I_d + \sum_{k=1}^4 \delta I_k P_{k,l} + \frac{1}{2} \sum_{k=1}^4 \delta^2 I_k P_{k,l}^2 \right]$$

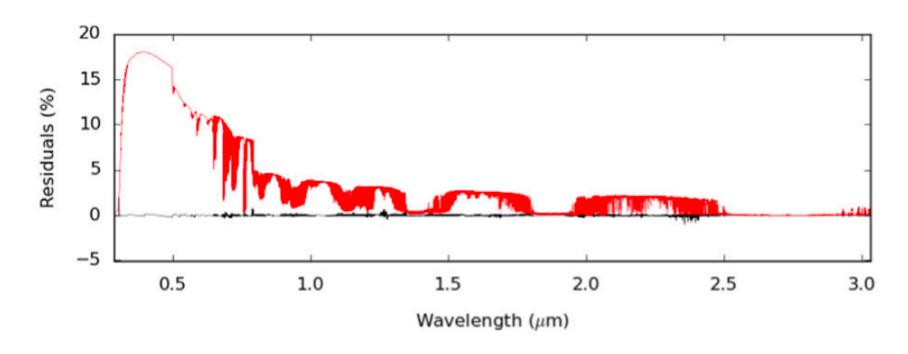
PCA Flowchart



Spurr et al., 2013



Broadband Radiances

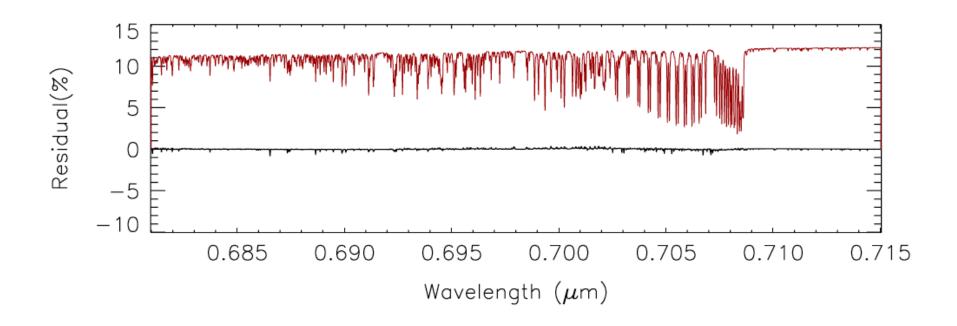


Red: Two-stream; Black: PCA

Kopparla et al., 2016



Zoomed in



Brown: Two-stream; Black: PCA

Kopparla et al., 2016

Radiance-Based PCA (Liu, X., et al.)

independent pieces of information << # channels

PCA performed on channel radiances

 Large number of atmospheric profiles used to generate a matrix of spectral channel radiances (done offline)

PCA produces EOFs (which are scenario independent)

 PC scores for specific scenario obtained using monochromatic calculations at selected wavelengths

Unified PCA

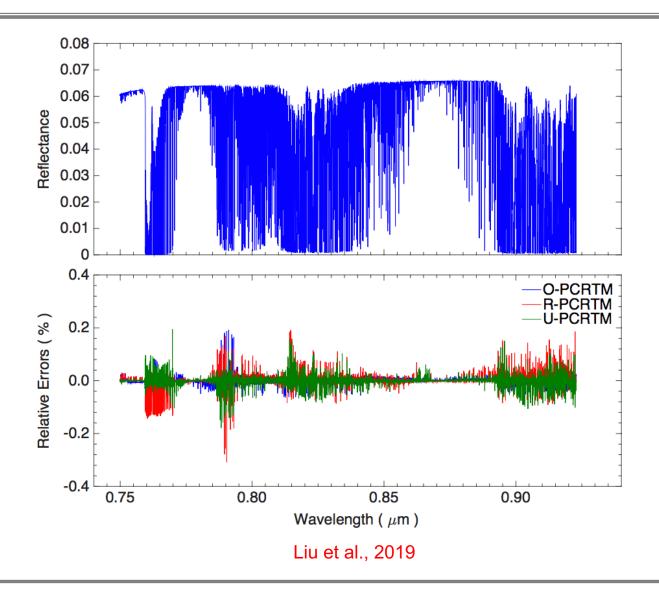
Optical-PCA minimizes number of RT calculations per instrument channel

 Radiance-PCA minimizes number of instrument channels for which RT calculations are performed

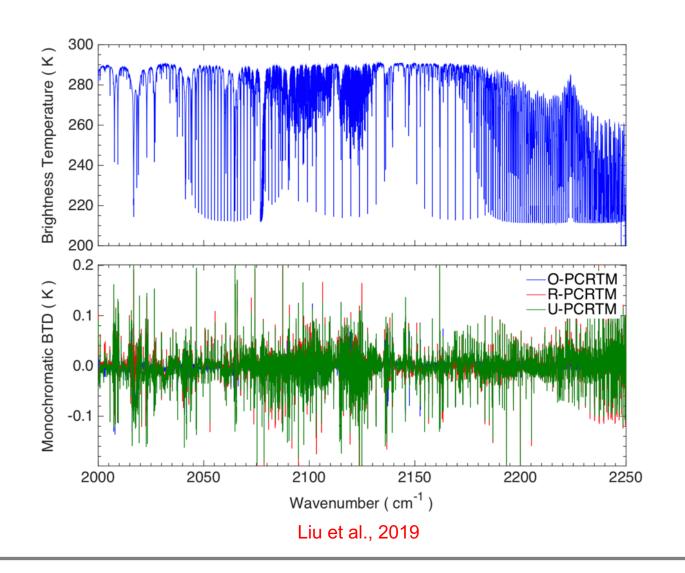
Two techniques are complementary

Unified PCA model would combine advantages of both methods

Unified PCA Example 1



Unified PCA Example 2



Future Work

Vertical layering

Spectral sampling

Binning

Polarization

Unified PCA

Remote sensing retrievals / climate models

Backup Slides

Overview of Existing Techniques I

Correlated-k/Exponential Sum Fitting of Transmittances

Widely used for atmospheric heating/cooling rate calculations

Assume that optical properties spectrally correlated at all points along optical path

Only valid for homogeneous, isobaric, isothermal atmospheres

Loss of correlation can introduce significant radiance errors

Overview of Existing Techniques II

Spectral Mapping

- No assumption about spectral correlation along optical path
- Perform level-by-level comparison of monochromatic atmospheric and surface optical properties
- Combine only spectral regions that remain similar at all points along inhomogeneous optical path
- Fine binning required to achieve high RT calculation accuracy
- Coarse binning provides significant reduction in radiance accuracy

Overview of Existing Techniques III

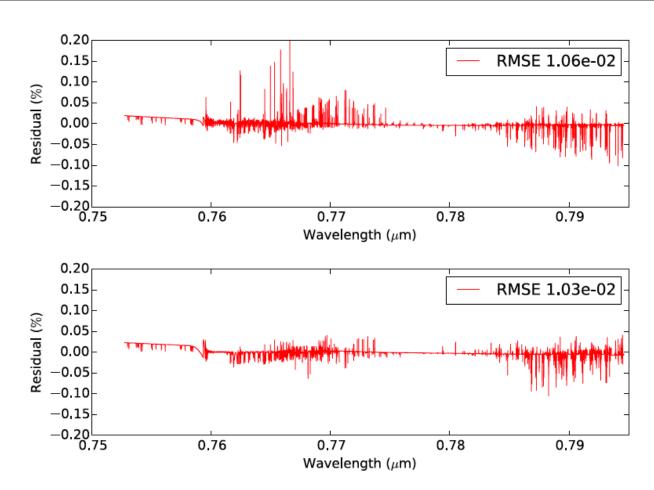
- Asymptotic Methods
 - Limited to study of semi-infinite media (e.g. optically thick clouds)

- Low Orders of Scattering
 - Restricted to study of optically thin atmospheres

- Others
 - Usefulness only proven for narrow spectral regions
 - Many of these techniques rely on finite differences



Vertical Grid

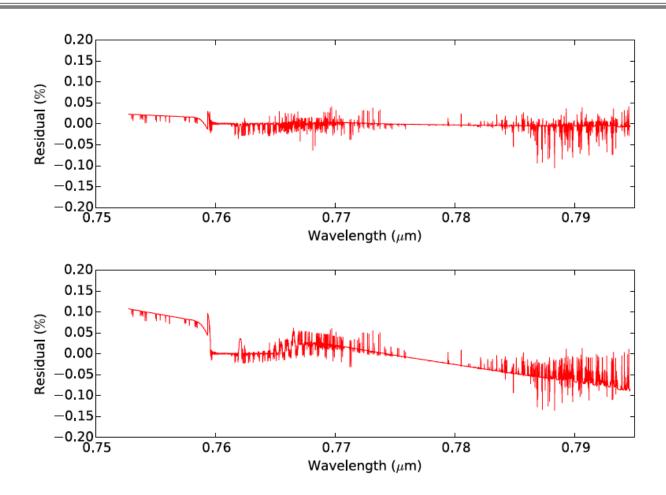


Top: Arbitrary grid; Bottom: Equal pressure thickness grid

Kopparla et al., 2017



Aerosols in the PCA

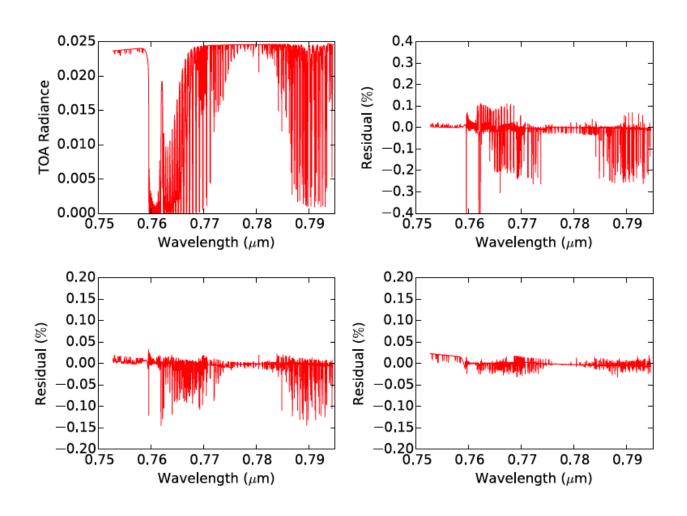


Bottom: Bin averaging for aerosol properties; Top: Aerosols in the PCA

Kopparla et al., 2017

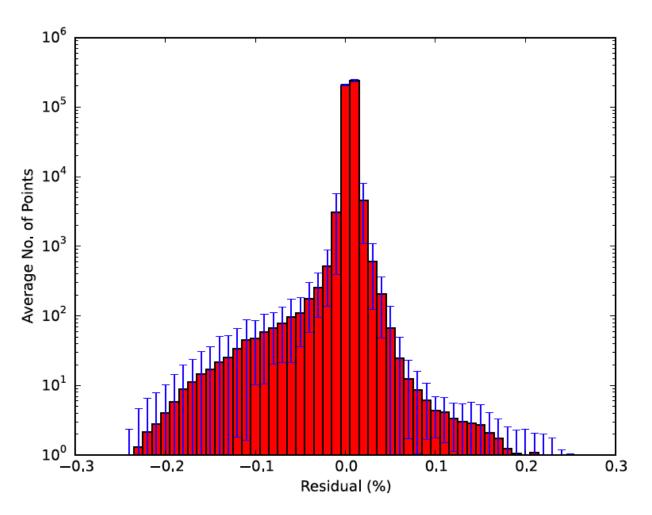


Binning Schemes



Kopparla et al., 2017

Distribution of Residuals



Kopparla et al., 2017